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Research Article

Alzheimer's Patient Support System Based on IoT and ML

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Abstract: Alzheimer's disease poses significant challenges as it progressively erodes memory and identity, severely impacting daily functioning. Patients often experience disorientation, wandering, and are at risk of falls, leading to heightened concerns for caregivers. These difficulties can result in a loss of independence and increased caregiver burden. In response to these challenges, this study introduces an innovative assistive system designed to enhance the safety and quality of life for Alzheimer's patients. The system comprises of two main components: a smart arm band and a facial recognition system. The smart arm band is equipped with a suite of sensors including GPS, accelerometer, and heart rate sensor. These sensors enable real-time monitoring of the patient's location, movement, and physiological parameters. By leveraging these data streams, caregivers can track the patient's activities, detect falls or emergencies, and provide timely assistance when needed. The facial recognition system employs state-of-the-art machine learning techniques, specifically the CAFFE and Local Binary Patterns Histograms (LBPH), to recognize familiar faces in the patient's environment. This capability promotes social interaction and enhances the patient's sense of familiarity and security. Through rigorous testing, the facial recognition system achieves an impressive accuracy of 97% with a low error rate of 3%, validating its effectiveness in real-world scenarios. Overall, the integrative assistive system presented in this study offers a promising solution to address the multifaceted challenges associated with Alzheimer's disease. This system provides caregivers with invaluable support in ensuring the safety and well-being of Alzheimer's patients while fostering social engagement and autonomy.

***Keywords*:** Alzheimer's disease, CAFFE, face recognition, IoT, LBPH, machine learning, performance matrix

Abbreviation

Term	Description
AD	Alzheimer's disease
CAFFE	Convolutional Architecture for Fast Feature Embedding
LBPH	Local Binary Pattern Histogram
IoT	Internet of Things
SVM	Support Vector Machines

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1. Introduction

Alzheimer's disease (AD) is a neurological disorder of extreme gravity that affects memory, cognition, and behaviour in a very complex way. The most common type of dementia, it gradually impairs several different brain functions before severely impairing everyday functioning. A complex interaction of components, including genetics [1, 2], protein buildup, and environmental/lifestyle factors, highlights the intricacy of Alzheimer's disease. The function of genetic predisposition is crucial in both familial and sporadic forms. In family situations, specific mutations are involved, but in the prevalent sporadic manifestation, the underlying genetic pattern is less clear. Diagnosing Alzheimer's disease (ADHD) requires a multidisciplinary approach that includes tests to evaluate cognitive function and rule out other possible disorders [3]. Cognitive exams are crucial to this diagnostic process. Two popular exams that thoroughly assess memory, language, attention, and visuospatial ability are the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA) [4].

As Figure 1 illustrates, there are essentially four stages of AD. People with severe AD have a significant and upsetting deterioration in their memory, cognitive function, and day-to-day abilities. This is known as the advanced stages of the disease. Significant loss of independence characterizes this key phase, which has a substantial effect on the person's overall quality of life [5, 6]. There are various symptoms experienced by Alzheimer's sufferers are depicted in Figure 2.

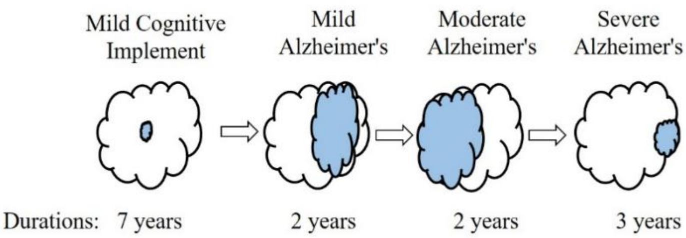

Figure 1. Stages of Alzheimer's disease [5].

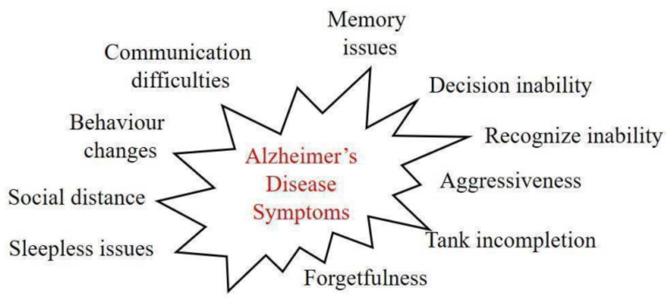

Figure 2. Symptoms of Alzheimer's patient [7].

Memory impairment is one of the most noticeable and early symptoms of AD. Even normal and familiar tasks might become difficult for persons with AD. Patients may experience confusion and disorientation, especially in strange settings. Language abilities can be negatively impacted by Alzheimer's, making it harder to grasp written or spoken language, follow discussions, or locate the appropriate words. They might display bad judgement, misplace things, struggle to stick to a schedule or finish chores that require multiple steps, lose their independence, and struggle to make decisions [7]. Enhancing the standard of living and encouraging self-sufficiency in those with disabilities can be greatly aided by an IoT-based support system. Key IoT support system aspects for AD are included in Table 1 as follows:

Table 1. Aspects of IoT devices extend support areas for AD.

Aspects	IoT Devices Extend Supports Areas
Availability	To provide support to those facing a range of obstacles, such as physical limitations, visual impairments, hearing impairments, and cognitive impairments.
Self-Determination	Technologies that offer remote help allow people to live more independently and manage their lives more skilfully.
Security and Safety	Combined with sensors and surveillance systems to improve security and safety, immediately alerting emergency services or caregivers to medical emergencies.
Tailored Assistance	To provide a customized support system in order to satisfy each person's unique demands and preferences.
Social Integration	Assist people in maintaining relationships with their friends, relatives, and online communities via systems, social media, video calls, and other means.
Better Health Care Administration	Help with communication with healthcare providers and health parameter monitoring.

A computer vision task called "Facial Landmark Detection" entails identifying and localizing certain points or landmarks on a face, like the lips, chin, nose, and eyes [8]. The face's geometry is interpreted by facial recognition as the space between your eyes and the length from forehead to chin are important measurements. The face recognition algorithm extracts feature from the image of the object of interest based on the facial traits it recognizes. Next, the obtained image and the surface data are contrasted [9]. Figure 3 depicts the general layout of a block diagram facial recognition system (FRS).

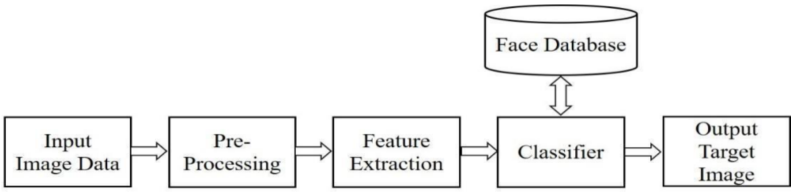

Figure 3. Block diagram of Face Recognition System [9].

The following list outlines the roles of the five major functional blocks [9].

- The Acquisition Module
- The Pre-Processing Module
    a. Normalizing the size of the image
    b. Eliminating the backdrop
    c. Translational and rotational normalizations
    d. Standardizing the lighting
- Module for Feature Extraction
- Module on Classification
- Face Database: It is employed to compare the train images kept in a database with the test image.

Alzheimer's disease poses distinctive challenges for patients and caregivers, necessitating novel approaches to enhance patient safety and well-being. This paper introduces a holistic system comprising a wristband with advanced features and a sophisticated face recognition system to address the complex needs of Alzheimer's patients and their caregivers. The system aims to provide effective support in managing patient safety, particularly during moments of vulnerability.

The primary goal of this system is to offer comprehensive assistance in addressing the safety concerns of Alzheimer's patients, especially during instances of disorientation, panic, or physical vulnerability. By integrating GPS, panic alert, and fall detection functionalities into the wristband, real-time monitoring and assistance are provided, mitigating risks associated with wandering and accidental falls.

Utilizing the BLYNK application as a central interface, caregivers can seamlessly track patient locations through GPS coordinates and receive instant notifications during emergencies. The panic alert system enables swift action during moments of distress, while the fall detection technology automatically notifies caregivers of any detected falls, ensuring timely intervention.

Furthermore, the face recognition component utilizes advanced algorithms like LBPH and CAFFE to facilitate patients in identifying familiar faces effortlessly. Integrated with the wristband, patients receive auditory cues through a headset, enhancing their sense of familiarity and comfort.

In conclusion, the proposed system offers a comprehensive solution tailored to the unique challenges faced by Alzheimer's patients and their caregivers. By combining advanced features within the wristband and leveraging cutting-edge face recognition technology, this system aims to enhance patient safety, improve caregiver response, and ultimately contribute to a higher quality of life for those affected by Alzheimer's disease.

The following is an outline of the remaining portion of this paper: Section 2 presents an overview of the literature, Section 3 provides an explanation of the methodology, and Section 4 offers some helpful mathematical modelling. Section 5 provides a description of the experimental analysis and its constituent parts. Section 6 has the conclusion.

2. Literature survey

Shiqi Chen et al. provided an overview of the usual uses of emerging IoT technologies in the healthcare industry. Numerous technologies, including sensing, networking, data management, artificial intelligence, and more, are envisioned for the Internet of Things [10].

Kalpana Devi studied a personal help system designed for those with AD. A list of people the patient has met is reminded of them. This aids the sufferer in getting over their difficulty identifying others [7].

Megh Pudyel and Mustafa Atay [11] carried out a thorough investigation in the field of face recognition in a different work, with a particular emphasis on mask-aware facial recognition. Their study examined a range of situations, such as the change from partially covered to completely covered or uncovered faces, helping to provide a thorough grasp of this process.

K. Jaspin, E. Ajitha, J. Dafni Rose, and K. Sherin [12] explored improvements to the Caffe model in a similar manner. Their evaluated system performed admirably within predetermined bounds, demonstrating advancements in this important field of study.

Furthermore, P Yashwanth Ram and B.A. Sabarish [13] developed face recognition systems by using a linear Support Vector Machine (SVM) face categorization method. This enhancement marks a noteworthy advancement in the precision and dependability of facial recognition algorithms.

Yassin Kortli et al. proposed the second contribution of the paper is the LBPH descriptor using the SVM classifier for the detection technique [14].

Table 2 is a wide and comprehensive literature review that sheds light on numerous approaches and improvements in facial recognition technology aimed at meeting the specific demands of Alzheimer's sufferers.

Table 2. Literature survey of the research project of Alzheimer's patients

Author	Paper	Year	Findings
Aseel Thamer Ebrahem, Marwa Mawfaq Mohamedsheet, Entisar Younis Abd Al-Jabbar, Warqaa H. Alkhaled, Zaid Husham Al-Sawaff	Using IoT technology for monitoring Alzheimer's and elderly patients	2023	A working prototype will identify AD patients in real time and send out an alert to remind them to take their medicine on schedule.
K. Jaspin, E. Ajitha, J. Dafni Rose, K. Sherin	Using the Caffe Model for an Intelligent Traffic Light Control System: An Approach Using Deep Learning	2023	Performing at ninety-five percent accuracy in object detection
Megh Pudyel, Mustafa Atay	An Inquiry-Based Analysis of Masked Facial Identification Using Machine Learning Techniques	2023	Developing the mask-aware face recognition system
P Yashwanth Ram, B.A Sabarish	Comparative Analysis and the Effect of Dimensionality Reduction in Face Recognition Using Machine Learning Models	2022	Better accuracy performance is obtained with logistic regression.
Kalpana D.S, Amirthavarshini D, Anbukani R S, Bhavatha R S	Alzheimer's patients' personal assistance	2020	App that provides patients with individualised support
Olufisayo S. Ekundayo; Serestina Viriri,	A Survey of Current Trends and Methods in Facial Expression Recognition	2021	Face Recognition (FER) in Three Different Machine Learning Frameworks.
Shivalila Hangaragia, Tripty Singh, Neelima N	Deep Neural Network with Face Mesh for Face Recognition and Detection	2023	Using Face mesh, the proposed model is able to identify and detect faces.
Rahaf Alturki, Maali Alharbi, Ftoon AlAnzi, Saleh Albahli	Deep learning methods for identifying and detecting face masks: An overview	2022	Deep learning algorithms identified the features that were covered.
Raktim Ranjan Nath, Kaberi Kakoty, Dibya Jyoti Bora	Algorithm for Machine Learning for Face Detection and Recognition	2020	More accurate findings are obtained with a face detector based on HOG.

3. Methodology

This research project has a significant mission: to create a complete assistance system specifically intended to suit the unique needs of people living with AD. This effort intends to build a strong support framework by leveraging cutting-edge technology such as facial recognition, GPS monitoring, a panic warning system, and an accelerometer.

Figure 4 displays the integration of the hardware system block diagram. Blynk app and panic warning system seamlessly combine all of the collected data, including facial recognition information, GPS position, heartbeat sensor readings, and accelerometer sensor readings. This smartphone app serves as a central location where family members and carers may get up-to-date information about the whereabouts and general well-being of Alzheimer's patients [15, 16]. The Blynk app's user-friendly UI makes it simple for users to keep informed and, in an emergency, take quick action. This involves Alzheimer's sufferers creating a loving and encouraging atmosphere for others impacted by this challenging condition.

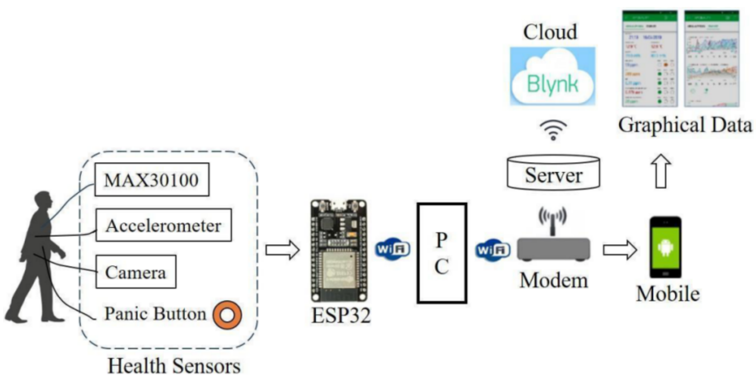

Figure 4. Block diagram of a hardware system.

The ESP8266 peripherals that are currently in use are listed in Table 3 along with their corresponding ratings. For instance, when the system is used stand-alone, only the heart rate sensor and accelerometer detect inputs; the camera only activates when the sensor data indicates that a face is going to appear. Module for communication: This consists of the IoT-Multi-Sensor unit's Wi-Fi access points connecting it to the IoT platform, which can be accessed through a PC's browser. Alzheimer's patients should be found within the roughly 50–60 meter Wi-Fi access point range.

Table 3. Hardware peripherals and current rating (mA) [15, 17]

Hardware Peripherals	Current Rating (mA)
ESP8266	250
Camera	250
Accelerometer	0.5
MAX30102 Pulse Oximeter and Heart Rate Sensor	20
HDMI port	50
Wi-Fi connection	250
Keyboard	100
Mouse	100
Total current consumption	**1020.5**

A facial recognition system is a computer program that may be automatically validated by an individual or recognized by a digital image or video source. There are several approaches to carrying out the detection or identification [17]. Comparing specific facial traits between the image and face database is one approach. In order to produce a finished Face Recognition project, it's necessary to focus on three distinct phases:

i. Data collection and facial recognition

ii. Train the Recognizer

iii. Face Recognition Stage

A facial recognition example is shown in Figure 5. The procedure begins with the camera carefully taking a picture of a person's face. To extract complex facial traits, this collected image is carefully processed. After the face has been successfully identified, relevant features like inter-eye distance and nose geometry are carefully isolated. These processed face features are then sent to a laptop or a small single-board computer that is well-known for being portable and versatile.

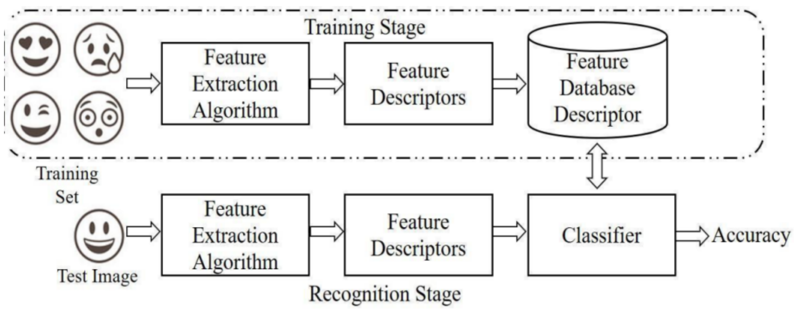

Figure 5. Facial recognition using Machine Learning.

The system carefully analyses the extracted facial features with those in its database by using complex algorithms. When a match is found, a signal is immediately sent to the headphones, causing an audio output that can be customised. Modern technology is seamlessly integrated into the system to give quick and precise recognition, allowing for customised replies based on the needs of the individual. The block diagram in Figure 6 depicts a facial recognition system.

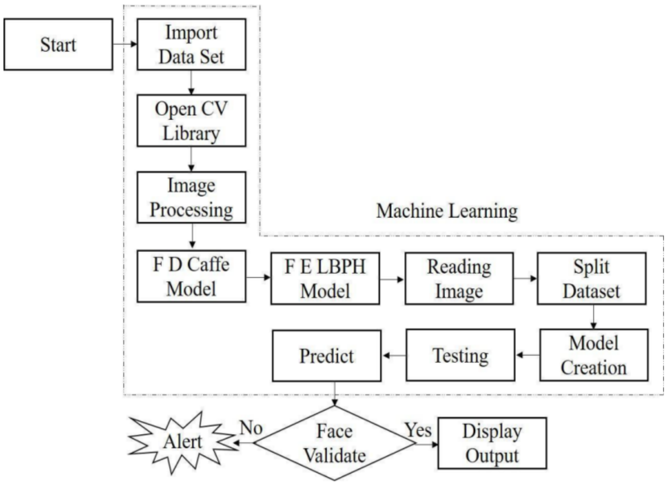

Figure 6. Facial recognition based on machine learning.

The three essential phases of face recognition step (FRS)—face detection, facial feature extraction, and face recognition of image. Following are the steps' descriptions:

FRS 1: A dataset is created by applying face detection to the input image.

FRS 2: An implemented library for face detection methods is included in OpenCV.

FRS 3: Classifiers are trained using training images.

FRS 4: By foreseeing the distinct face in testing images, the algorithm is validated.

The recognition result provides the person's identity.

The following performance matrix is identified by the facial recognition system using machine learning in the aforementioned processes.

3.1 *Training*

Metrics like recall, accuracy, and precision are frequently used to evaluate the effectiveness of a facial recognition system that has been trained using LBPH (Local Binary Patterns Histograms) in conjunction with the CAFFE model. These metrics have the following mathematical definitions [18, 19]:

3.1.1 *Accuracy*

Accuracy is defined as the percentage of the total number of samples that the model correctly predicted. Equation (1) determines the model's classification accuracy.

$$Accurancy = (TP + TN) / (TP + FP + FN + TN) \tag{1}$$

where:

TP stands for true positives, or anticipated occurrences.

TN stands for genuine negatives, or anticipated occurrences.

FP stands for false positives, or expected cases.

FN stands for false negatives, or anticipated occurrences.

3.1.2 *Precision*

The ratio of correctly anticipated positive observations to the total number of predicted positive observations is known as precision. The classification precision value is provided by Equation (2).

$$Precision = (TP) / (TP + FP) \tag{2}$$

3.1.3 *Recall (Sensitivity)*

Recall is the proportion of true positive forecasts to all actual positive events. Equation (3) provides the classification's recall value.

$$Recall = (TP)/(TP + FN) \tag{3}$$

3.1.4 *F1-Score*

F1-score takes into account both false positives and false negatives. The classification's F1-score is calculated using Equation (4).

$$\mathrm{F1-score} = (2 \times Precision \times Recall)/(Precision + Recall) \tag{4}$$

3.1.5 *Error rate*

The number of incorrectly identified samples from both +ve and −ve classes is the error rate accuracy. Error rate for the classification model is given by Equation (5).

$$Error\ Rate = 1 - Accurancy \tag{5}$$

In the context of facial recognition model:

TP: it recognizes a person's face accurately by the model.

TN: non-face region is accurately rejected by the model.

FP: non-facial region is mistakenly identified as a face by the model (False Alarm).

FN: model is unable to recognize a face in the picture.

Once the facial recognition system has been trained and tested, compute these metrics using our model's predictions on a different test dataset, along with ground truth labels. To compute these metrics, the predictions from the LBPH algorithm and the CAFFE model are compared with the ground truth labels.

4. Mathematical modelling

The process of finding and identifying human faces in digital photos and videos is known as face detection, or facial recognition, and it is based on artificial intelligence (AI). Using machine learning methods, features in an image detects faces. It detects additional face features after searching the database. Once a face has been identified, it verifies by comparing these features to training data. In this research project, the following face detection models are partially used:

4.1 *Local binary patterns histograms (LBPH):*

For face identification, the Local Binary Pattern Histogram approach is employed. In order to reduce the local spatial dispersion of a face image, the Local Binary Patterns (LBP) operator applies local binary patterns [20]. About 8 pixels make up the LBP operator, which is a collection of binary pixel value ratios arranged in the middle at regular pixel intervals as the equation below [21].

4.1.1 *Local binary patterns (LBP):*

LBPH computes a binary code for each pixel based on the intensity values of its neighbouring pixels. Let $I(x, y)$ represent the intensity value of the pixel (x, y) in the input image. Given a pixel (x_c, y_c) with 'P' neighbouring pixels and radius 'R', the Local Binary Pattern (LBP) is calculated as:

$$LBR_{P,R}(x_c, y_c) = \sum_{p=0}^{p=1} s(I(x_p, y_p) - I(x_c, y_c)) \times 2^p \tag{6}$$

where $s(x)$ is a function that returns 1 if x is non-negative and 0 otherwise, and (x_p, y_p) are the coordinates of the neighbouring pixels.

The summation ranges from 0 to $P - 1$ because:

1. Indexing Neighbouring Pixels: The PP variable represents the index of the neighbouring pixel around the central pixel (x_c, y_c). In a circular neighbourhood with radius R, there are typically P neighbouring pixels. These neighbouring pixels are indexed from 0 to $P - 1$.

2. Contributions to Binary Code: Each neighbouring pixel contributes to the binary code of the central pixel. The intensity difference between the central pixel and each neighbouring pixel is compared, and based on whether the difference is positive or negative, a binary value (0 or 1) is assigned. This binary value is then multiplied by 2^P, where P represents the position of the neighbouring pixel in the circular neighbourhood.

3. Summation: The summation aggregates the contributions from all neighbouring pixels, each weighted by 2^P. By summing these contributions over all P neighbouring pixels, we obtain the final binary code for the central pixel.

4.1.2 *Histogram calculation:*

The LBP values are used to construct a histogram HLBPH, where each bin represents the count of pixels with a specific LBP value. Mathematically, the histogram can be represented as:

$$HLBPH\,(i) = count\ of\ pixels\ with\ LBP\ value\ i \tag{7}$$

where i, ranges from 0 to $2^P - 1$, covering all possible LBP patterns.

In the LBPH approach, after computing the Local Binary Patterns (LBP) for each pixel, these patterns are used to construct a histogram. Each bin in the histogram represents the count of pixels with a specific LBP value.

The LBP value for a pixel range from 0 to $2^P - 1$ because it is represented as a binary number with P digits. Each digit can be either 0 or 1, hence there are 2^P possible combinations of binary patterns.

4.2 *CAFFE feature extraction:*

CAFFE (Convolutional Architecture for Fast Feature Embedding) is a deep learning framework supports several deep learning architectures, incorporating fully connected networks, LSTM, CNN, and RCNN. The Caffe framework is being developed by community members and Berkeley AI Research (BAIR). Caffe is being used in large-scale industrial applications in multimedia, voice, and vision as well as in research projects at universities and start-up companies. CAFFE, a deep learning framework for machine learning, is accessible as open-source software [22].

4.2.1 *Preprocessing*

Preprocessing steps are applied to the input image before feeding it into the CAFFE model. This may include resizing the image, normalization, and colour space conversion.

$$I_{Preprocessed} = Preprocess\,(I) \tag{8}$$

where, 'I' represents the input image, and $I_{Preprocessed}$ denotes the pre-processed image.

This equation represents the preprocessing step applied to the input image I before feeding it into the CAFFE model.

The preprocessing step typically involves several transformations to prepare the image for feature extraction. These transformations may include:

1. Resizing: Ensuring that the image has a consistent size suitable for input into the CAFFE model. This might involve resizing the image to a fixed width and height.

2. Normalization: Adjusting the pixel values of the image to a standardized range. Normalization often involves scaling the pixel values to lie within a certain range (e.g., 0 to 1 or -1 to 1).

3. Colour Space Conversion: Converting the colour space of the image if needed. For example, converting from RGB to grayscale or converting to a different colour space like YUV or LAB.

The output of the preprocessing step, $I_{Preprocessed}$, is the modified image ready to be passed into the CAFFE model for feature extraction. This ensures that the input data is in a suitable format for the model to process effectively.

4.2.2 *Feature extraction:*

The preprocessed image is passed through the pre-trained CAFFE model to extract features.
Let F_{CAFFE} represent the extracted features.

$$F_{CAFFE} = CAFFE\left(I_{Preprocessed}\right) \tag{9}$$

This equation represents the process of feature extraction using the CAFFE model on the preprocessed image $I_{Preprocessed}$

F_{CAFFE}: This represents the extracted features obtained from the CAFFE model. These features capture important patterns and characteristics present in the input image.

CAFFE: This refers to the CAFFE model, which is a deep learning framework commonly used for image classification, object detection, and feature extraction tasks. The CAFFE model is pre-trained on large datasets to learn hierarchical representations of visual features.

$I_{Preprocessed}$: This denotes the preprocessed image obtained after applying various transformations such as resizing, normalization, and colour space conversion. Preprocessing ensures that the input image is in a suitable format for the CAFFE model to process effectively.

When the preprocessed image $I_{Preprocessed}$ is inputted into the CAFFE model, the model applies a series of convolutional, pooling, and activation operations to extract features that are relevant for the task at hand. These features are then aggregated and represented in the output F_{CAFFE}.

4.3 *Combining features:*

The features extracted from LBPH and CAFFE are combined into a comprehensive feature vector $F_{Combined}$ for face recognition.

$$F_{Combined} = [F_{LBPH}, F_{CAFFE}] \tag{10}$$

This equation represents the combination of features extracted from the LBPH and CAFFE into a single comprehensive feature vector.

$F_{Combined}$: This denotes the combined feature vector that includes features from both the LBPH method and the CAFFE model. By combining these features, we aim to capture a broader range of information about the input image, enhancing the model's ability to discriminate between different faces.

F_{LBPH}: This represents the feature vector obtained from the LBPH method, which encodes local texture information based on the distribution of local binary patterns in the image. Each element of FLBPH corresponds to the count of pixels with a specific LBP value, as calculated from the histogram of LBP patterns.

F_{CAFFE}: This denotes the feature vector extracted from the CAFFE model, which captures high-level semantic features learned from deep convolutional neural networks.

By concatenating F_{LBPH} and F_{CAFFE} together into a single feature vector, $F_{Combined}$ we create a more comprehensive representation of the input image that encompasses both low-level texture information (from LBPH) and high-level semantic features (from CAFFE). This combined feature vector can then be used for subsequent tasks such as face recognition, where the model needs to identify and distinguish between different individuals based on their facial characteristics.

The above refined mathematical modelling equations of the CAFFE+LBPH approach outlines the steps involved in computing LBP patterns, constructing histograms for local texture information using LBPH, preprocessing the input image and extracting features using the CAFFE model, and combining these features into a comprehensive feature vector for face recognition.

5. Results and analysis

The movement of Alzheimer patients is monitored in this paper using several types of sensors, actuators, and machine learning techniques. To ensure that the information about these patients' health is accurate, a variety of IoT device types are used for their health monitoring.

5.1 *Performance discussion of the hardware device*

The entire research project was carried out using a laptop with an Intel(R) Core (TM) i3-1005G1 CPU processor with 1.2 GHz, 8 GB of RAM, and an x64-established operating system running a 64-bit operating system. The Jupyter Notebook tools and the Python 3.9 version kernel were used to implement machine learning for the proposed paper. Figure 7 depicts the IoT-Multi-Sensor, which is part of the hardware architecture of the proposed system.

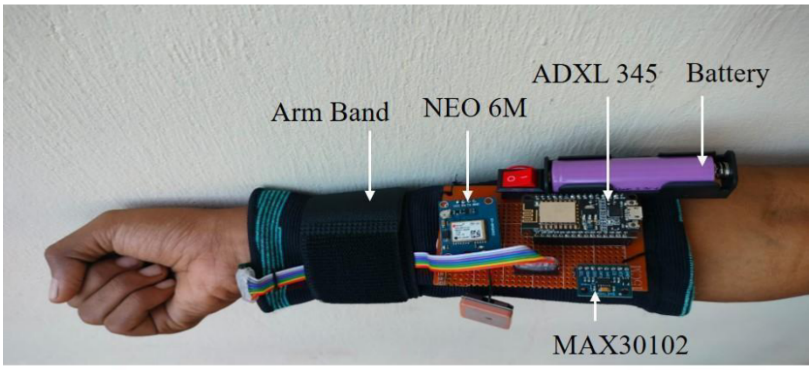

Figure 7. System Arm-Band.

The proposed hardware implementation consists of (i) the NEO 6M GPS module, and (ii) The MAX30102 Heart Rate Sensor (iii) ADXL 345 accelerometer sensor, and (iv) ESP32 microcontroller. These peripherals are placed on an Arm Band and powered by a battery.

The hardware implementation of the armband setup is meticulously crafted to seamlessly integrate essential features such as GPS tracking, fall detection, and panic alert systems, all aimed at providing comprehensive assistance and monitoring for Alzheimer's patients, while prioritising their safety and well-being.

Designed with practicality and user comfort in mind, the armband is engineered to be compact and lightweight, ensuring that the wearer can comfortably wear it throughout the day without any inconvenience. Additionally, the inclusion of a rechargeable battery further enhances the portability of the device, allowing for extended usage without the need for frequent recharging.

At the heart of the hardware setup lies the ESP8266, serving as the main microcontroller that orchestrates the seamless operation of all integrated functionalities. The NEO6MV2 GPS module plays a pivotal role in location tracking, providing accurate real-time positioning data to caregivers and enabling prompt response in case of wandering incidents.

For the vital task of fall detection, the ADXL345 accelerometer is employed, leveraging its high sensitivity and precision to detect sudden changes in acceleration indicative of a fall. This component acts as a crucial safeguard, automatically triggering alerts to caregivers in the event of a fall, ensuring prompt assistance can be provided to the patient.

Furthermore, the MAX30102 sensor adds another layer of functionality by facilitating heart rate sensing, which not only provides valuable health monitoring capabilities but also contributes to the panic alert system. Abnormal fluctuations in heart rate can trigger immediate alerts, allowing caregivers to swiftly address any potential medical emergencies or moments of distress experienced by the patient.

To ensure user control and convenience, a power button is integrated into the design, enabling the wearer to easily manage the electrical flow within the circuit and conserve battery power when necessary. Coupled with a reliable Li-ion battery for power supply, the hardware setup is optimised for efficiency, longevity, and user-friendliness, embodying a holistic approach to Alzheimer's patient care and safety.

The wristband emerges as a pivotal tool in Alzheimer's care, offering unparalleled advantages distinct from conventional mobile phones. Amidst the complexities Alzheimer's presents, wherein patients grapple with intricate devices such as smartphones, the wristband emerges as a pragmatic solution. Its user-friendly design and streamlined functionality facilitate effortless use for both patients and caregivers, ensuring consistent monitoring and assistance. By embracing the wristband, caregivers can safeguard the welfare of their loved ones without depending on technologies that Alzheimer's patients may find challenging to operate. Looking ahead, the integration of VLSI technology within wristbands holds promise in further reducing their size and enhancing their efficacy.

5.1.1 *Peripherals sensors plots*

The Figure 8 shows the heart rate and accelerometer reading of the sensors. The patient's heart rate is plotted in real time. This displays the BPM (beats per minute) and charts the IBI (inter-beat interval) over time. The accelerometer plot displays the gap in reading that is apparent in the plot when the Alzheimer patient collapses or becomes frightened.

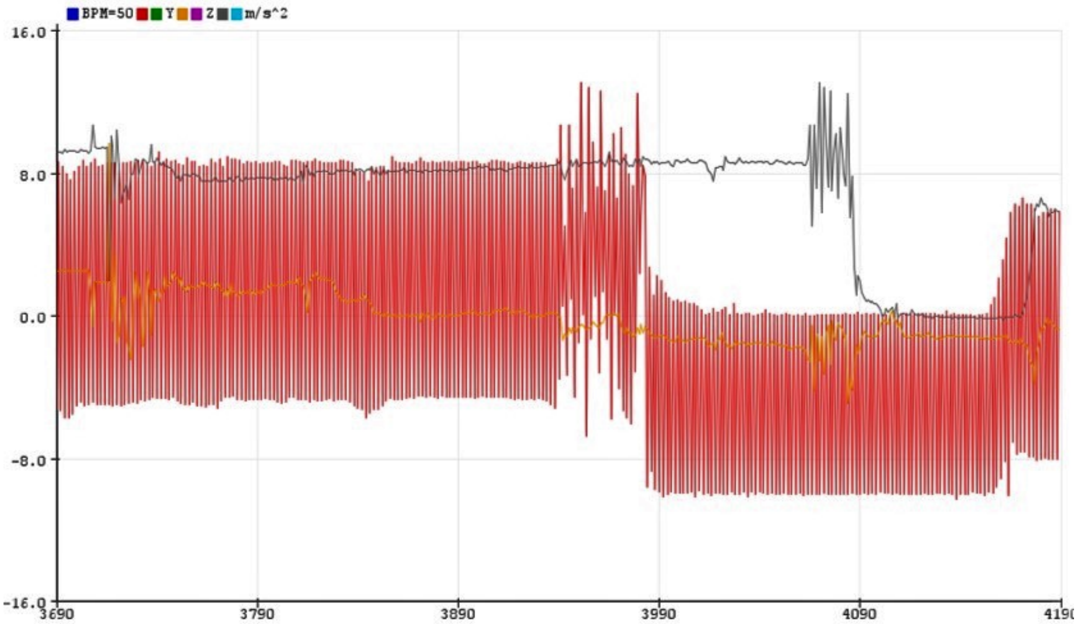

Figure 8. Heart Rate and Accelerometer plot.

5.1.2 *Oximeter and sphygmomanometer reading*

The Table 4 shows the distinct light emission and absorption of the deoxygenated and oxygenated form configurations is the basis for the operation of the oximeter.

Table 4. Data collected from an Oximeter.

Time(s)	Oxygen Saturation (%)	Pulse Rate (BPM)
0	97	72
5	96	71
10	95	69
15	96	70
20	98	73

Table 5 indicates that the sphygmomanometer's description can be found in numerous foundational texts on medical instruments and physiology (Geddes 1970, Webster 1997).

Observations:

- Moderate anxiousness was seen during the assessment procedure. The person seemed uncomfortable and expressed worries regarding the blood pressure results.
- Physical Condition: There were no indications of pain or discomfort.

Analysis:

- Blood pressure values should be interpreted with caution. Elevated diastolic and systolic readings suggest hypertension. The heart rate was within typical bounds.
- Fluctuations Caused by Anxiety: Variations in blood pressure measurements can be linked to an individual's anxiety during the measuring procedure.

Table 5. Sphygmomanometer Readings.

Measurement	Systolic BP (mmHg)	Diastolic BP (mmHg)	Heart Rate (BPM)
1st Reading	137	88	77
2nd Reading	139	90	81
3rd Reading	142	91	82

5.2 *Performance discussion of the proposed CAFFE-LBPH model*

Introducing the Smart Cap in Figure 9 for Alzheimer's patients: integrating a discreet camera for face recognition, it provides invaluable assistance in recognizing familiar faces. Designed to alleviate the challenges of memory loss, this innovative cap enables patients to identify loved ones, caregivers, and friends with ease. By analysing faces in real-time, it offers reassurance and security, enhancing their ability to engage meaningfully with those around them. With the Smart Cap, Alzheimer's patients gain independence and confidence, fostering connections and enriching their quality of life. It's a compassionate solution where technology meets empathy, making a meaningful difference every day.

Figure 9. Smart Cap.

CAFFE-LBPH's performance has been calculated using Accuracy, Sensitivity, and Specificity metrics. These measured values are categorised as true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

5.2.1 *Performance matrix table*

Table 6 presents a comparison analysis of performance metrics for multiple image samples. The various performance metrics are tabulated for picture numbers ranging from 50 to 1000.

Table 6. Comparison analysis of performance matrix for various images.

No. Of Images	TP	TN	FP	FN	Accuracy	Precision	Recall	F1-score	Error rate
50	30	5	10	5	70	75.0	85.7	80.0	30
100	75	5	10	10	80	88.2	88.2	88.2	20
200	169	1	15	15	85	91.8	91.8	91.8	15
400	372	3	10	15	93.75	97.4	96.1	96.7	6
800	770	0	15	15	96.25	98.1	98.1	98.1	4
1000	970	0	15	15	97	98.5	98.5	98.5	3

Table 7 Shows the comparison analysis of performance metrics for 1000 images samples with respect to the three models CAFFE-LBPH, CNN and HAAR CASCADE.

Table 7. Comparison analysis of performance metrics for 1000 images.

Performance Matrix	CAFFE-LBPH	CNN	HAAR CASCADE
Accuracy	97	97.5	90
Sensitivity	98.27	98	91
Precision	98.43	98	90

In this section, we compare the three strategies for facial recognition. Among these, the CNN has greater accuracy, sensitivity, and precision than the other two. However, we picked LBPH over CNN because CAFFE-LBPH is simpler and less computationally expensive. This could be useful if you have low processing resources. As a result, CAFFE-LBPH is giving an accuracy of 97%, Sensitivity of 98.27 and Precision of 98.43 in all aspects.

Thereby the results reveal that CAFFE-LBPH successfully captures texture-based information, which could be useful for distinguishing between faces. CAFFE-LBPH is faster than the other two in real-time applications.

5.2.2 *Performance matrix of images vs. training data*

A face recognition system's changing performance metrics as the quantity of images changes are depicted in Figure 10 of the accompanying graph.

Figure 10. Performance metrics plot of FRS images.

The system first demonstrated 70% accuracy with remarkable 75% precision and 85.7% recall out of 50 images. This illustrates the extent to which the system can recognize people while catching a substantial percentage of genuinely content events. With 1000 photos in the dataset, the system showed impressive growth: 97% accuracy, 98.5% precision and recall, and a 98.5% F1-score were all attained.

The pattern that has been noted indicates that better performance is facilitated by larger datasets, making it possible to distinguish faces from non-faces with greater accuracy.

5.2.3 *Performance matrix of images vs. training separately*

Figure 11 of the following graph shows the changing performance metrics of a face recognition system separately for the number of image groups.

Performance metrics consistently displayed an upward trend as the number of photos reached 100, 200, 400, 800, and 1000. The F1-score, recall, accuracy, precision, and error rate all exhibited increases that were positive. Based on a bigger sample size, this suggests that increasing values indicate improved performance and a decrease in errors.

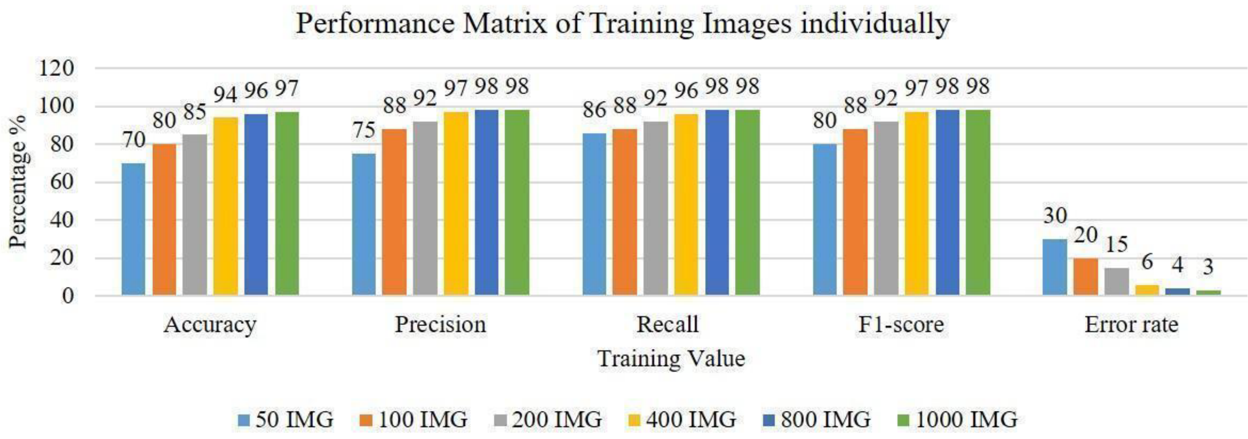

Figure 11. Performance metrics separate plot w.r.t number of images.

5.2.4 *Performance of various model vs. number of images [23]*

Performance plot of model w.r.t number of images is shown in Figure 12. In contrast to HAAR Cascade's performance, LBPH and CNN show comparable accuracy percentages in the bar plot of Accuracy vs. Number of images for CAFFE-LBPH, CNN, and HAAR Cascade.

A positive connection is implied by the direct proportionality that has been observed between accuracy and the number of images. LBPH attained 85% accuracy at 200 photos, CNN attained 90%, while HAAR Cascade trailed at 70%; over 1000 images, these figures improved to 97%, 97.5%, and 90%, respectively. Surprisingly, error rates for CAFFE-LBPH dropped significantly, from 30 at 50 photos to 3 at 1000 images.

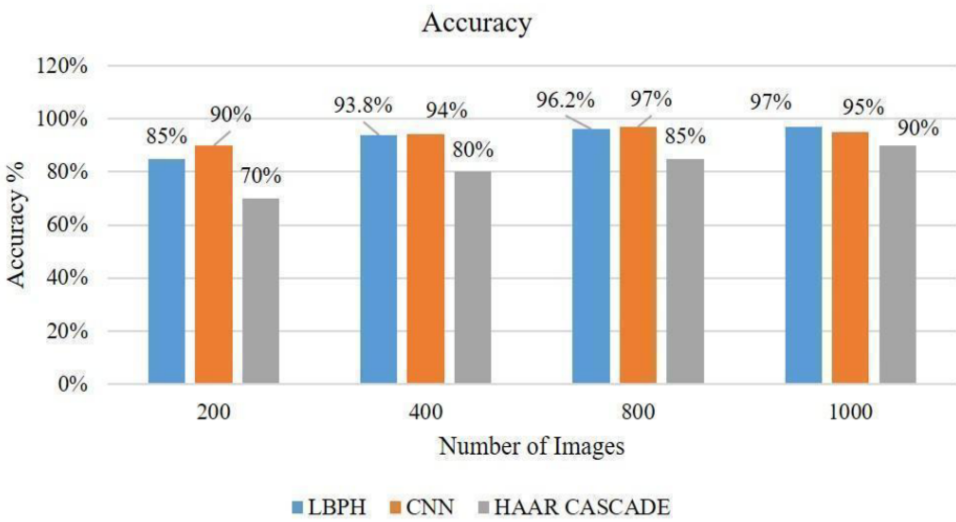

Figure 12. Performance metrics on Accuracy for different models.

The simplicity, interpretability, and computational efficiency of CAFFE-LBPH make it an acceptable choice even though CNN has the best accuracy. As a conventional image processing method, CAFFE-LBPH works well in situations where it is important to comprehend the decision-making process but computational power is constrained. CAFFE-LBPH provides an ideal choice for situations with limited resources or applications that prioritise interpretability, as evidenced by the decrease in error rates.

5.2.5 *Precision performance measures for various models*

Figure 13 illustrates precision performance metrics for a range of models. The precision percentages for CAFFE-LBPH, CNN, and HAAR Cascade are shown in a bar plot that contrasts Precision vs. Number of images.

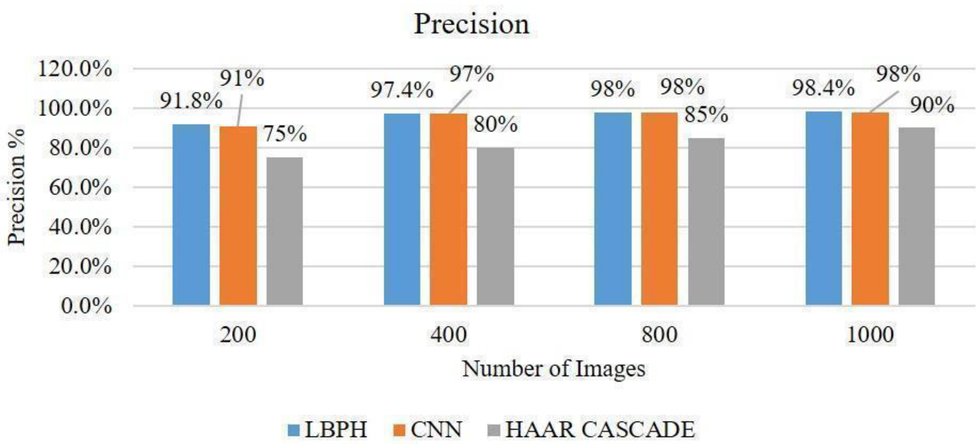

Figure 13. Performance metrics on Precision for different models

It is clear that precision directly correlates with image count. Now that we have 200 images, we can see that the precision was 91.8% for CAFFE-LBPH, 91% for CNN, and 75% for HAAR Cascade. After 1000 photographs, the precision increased to 98.44% for CAFFE-LBPH, 98% for CNN, and 90% for HAAR Cascade. While CNN is a black-box system that makes interpretation difficult and may result in lesser precision, CAFFE-LBPH's interpretability, which is based on local pattern analysis, helps in fine-tuning for improved precision.

5.2.6 *Performance metrics on sensitivity for different models*

Figure 14 depicts the sensitivity performance measures for several models. The bar plot Sensitivity vs. Number of pictures for CAFFE-LBPH, CNN, and HAAR Cascade demonstrates that LBPH and CNN have equal sensitivity to HAAR Cascade. The observed direct correlation between the quantity of pictures and sensitivity suggests a positive link. CAFFE-LBPH had 91.8% sensitivity at 200 images, CNN had 92%, and HAAR Cascade had 75%, which improved to 98.44%, 98%, and 90% at 1000 photos, respectively.

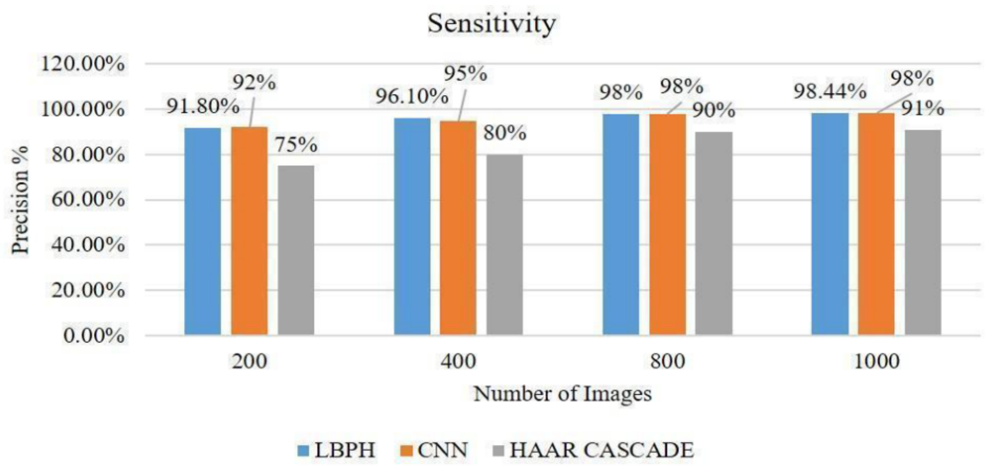

Figure 14. Performance metrics on Sensitivity for different models

The choice of CAFFE-LBPH is based on its ability to take use of local texture patterns, which works well in settings with little data. Unlike CNNs, which may have trouble with complex patterns and variations, CAFFE-LBPH outperforms them in terms of sensitivity to illumination variations and facial expressions. Sensitivity is vital for successful detection under varied situations. The interpretability of CAFFE-LBPH enhances sensitivity even more by providing transparency for decision-making and enabling efficient model modifications. To sum up, CAFFE-LBPH proves to be a reliable option for face recognition, demonstrating exceptional sensitivity, particularly in limited data environments.

5.2.7 *Confusion matrices of proposed model*

The display of the generalised confusion matrices is shown in Figure 15a,b respectively, for the suggested model's categorization. Based on the obtained metrics, including accuracy, precision, recall (or) sensitivity, f1-score, and error rate, the suggested CAFFE-LBPH approach was assessed.

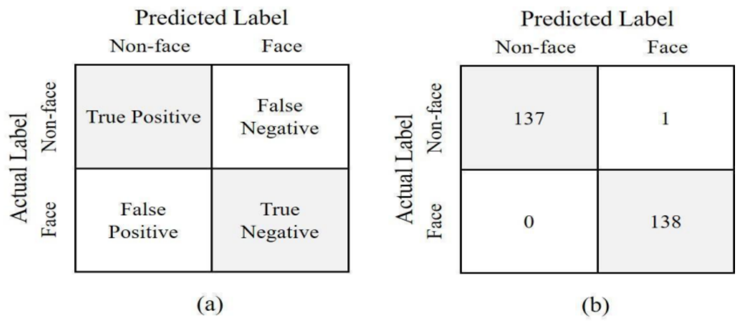

Figure 15. (**a**) Confusion matrix of standard form, (**b**) Confusion matrix of CAFFE-LBPH proposed model.

The values of TP (137), TN (138), FP (0), and FN (1) can readily be observed in Figure 15b. Our research concludes that the total accuracy of the model was 99.64%, and FP value is 0 for precision calculations. Confusion matrix values are substituted into Equation (2) in our manuscript to yield the 100% precision value.

6. Conclusions

The proposed innovation involves the development and implementation of an advanced face recognition model alongside a smart armband equipped with GPS, heartbeat sensor, and accelerometer for comprehensive care of Alzheimer's patients. The BLYNK application serves as a centralized hub for monitoring patient location, receiving alerts for falls and emergencies, and accessing vital real-time data.

Integration of the Caffe and LBPH models enables Alzheimer's patients to identify familiar faces, fostering a sense of security and familiarity. Results demonstrate the system's impressive accuracy of 97% and a low error rate of 3% achieved during testing on a 1000-image dataset underscores its reliability in practical applications. This level of precision instils confidence in caregivers and patients alike, fostering a sense of security and trust in the technology's ability to support their needs effectively. Such high accuracy not only enhances patient safety but also streamlines caregiving efforts, allowing for more efficient allocation of resources and timely interventions when necessary. As a result, caregivers can approach their responsibilities with greater confidence, knowing they have access to a dependable tool that prioritizes patient well-being. This level of precision sets a new standard in Alzheimer's care, paving the way for future advancements and innovations in the field.

Future enhancements include AI-driven improvements to the face recognition model, refinement of the smart cap's design, and expansion of the smart armband's capabilities. Additionally, exploring real-time data analysis and prediction algorithms for early detection of distress indicators holds promise for further system enhancement and validation. Continuous updates and integration of user feedback are crucial for driving ongoing improvement and widespread adoption of this innovative solution. Embracing a philosophy of continual refinement and user-focused design is essential to unlocking the full potential of this technology, ultimately delivering long-term benefits for Alzheimer's patients and their caregivers.

Conflict of interest

There is no conflict of interest for this study.

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